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SOME EMPIRICAL ISSUES IN THE ESTIMATION OF MARKET VALUES OF ENVIRONMENTAL AMENITIES

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ABSTRACT

This study presents consistent, and more efficient estimates compared with OLS and IV, for market values of amenities. The gain in efficiency is based on the use of a number of different indicators for the same amenity. The theory is derived from on a Lancasterian model that forces the functional form to be linear in characteristics. The empirical structure based on latent variables is applied to a model on property values of residential housing using different indicators for neighborhood quality. The dependent variable (property market value) is also treated as a latent variable for which two measures are available. The model is estimated using data from the U.S. American Housing Survey. The effect of quality of neighborhood on property values consistently estimated, is positive and significant. Variances of errors of measurement, and variances of the latent structures are positive and significant without imposing nonnegativity restrictions.

RESUMEN

Este estudio presenta estimaciones consistentes, y más eficientes comparadas con MCO y VI, de valores de mercado de bienes ambientales (amenities). La ganancia en eficiencia está basada en el uso de varios indicadores para el mismo bien. La teoría se deriva de un modelo Lancasteriano, que impone la linealidad en características de la forma de la ecuación de precio. La estructura empírica basada en variables latentes es aplicada a un modelo sobre valores de propiedad residencial usando diferentes indicadores de calidad de vecindario. La variable dependiente (valor de mercado de la propiedad) está tratada también como una variable latente para la cual se utilizan dos mediciones. El modelo se estima con datos provenientes de la encuesta de hogares en EE.UU. (U.S. American Housing Survey). El efecto de calidad de vecindario sobre el valor de la propiedad estimado en forma consistente, es positivo y significativo. La varianza de los errores de medida, y las varianzas de las estructuras latentes son positivas y significativas sin imponer ninguna restricción de no negatividad.

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Some Empirical Issues in the Estimation of Market Values of Environmental Amenities

1 Introduction

The issue of measurement of environmental improvements has important policy implications as has been pointed out, for instance, in Bartik and Smith (1987), Baumol and Oates (1988), Smith (1990), and more recently in Cropper and Oates (1992). Adequate measures of the demand for environmental quality provide an indication of the dollar value placed on benefits of environmental programs. Smith (1990) presents a very clear description of the problem facing the analyst that needs to measure implicit prices values that individuals impute when they consume services provided by environmental amenities. Traditional methods to value site amenities include two major approaches: the hedonic framework and discrete choice models.

One still unsolved issue in the hedonic approach is the lack of consensus about an appropriate measure for amenities. Attempts to measure amenities have concentrated in either proxy variables or direct measures. Proxy variables such as crime rate, recreational opportunities, etc., are usually included in a regression of prices on attributes [e.g. Witte, Sumka and Erekson (1979), Dubin and Sung (1990)]. However, there is not a unique measure for the same amenity. Hence, the issue becomes how to choose the best measure. Also, the measure for the amenity is only an indication of consumer's perceptions, and therefore, an imperfect measure. The literature has been ignoring these two issues, which caused loss of information that derived into biased estimates in all different implicit prices of characteristics.

The purpose of this study is to provide estimates of the effects of environmental amenities on housing values, using a known procedure that takes advantage of the existence of multiples indicators in the presence of latent variables. Data for the estimation of this model consist of samples obtained from the American Housing Survey. I estimate market values of amenities based on a number of different indicators for the same amenity and compare results with a model that uses a more traditional approach, i.e., with a model that considers one measure for an amenity a simple proxy variable. In particular, I focus on different indicators for neighborhood quality.

This study presents results on property values of residential housing using a methodology

that has not been applied in the field. It has the significant advantage of incorporating additional information on individual's perceptions of environmental amenities for the estimation of their market values. A special statistical treatment of the dependent variable (housing prices) when it is expressed as household's perceptions and not current market prices is included in the analysis. The functional form of the price equation is treated under special conditions that force that equation to be linear in characteristics.

2 Measuring amenities and their market value

The empirical issues in relation with the product "amenity" can be categorized into: (a) Data problems, i.e, difficulties in the measurement of amenities, and (b) Estimation problems, i.e., what methods are available to improve the estimation of market values of amenities. The final goal of these estimations is to provide measures that can be used to evaluate the benefit (and costs) of changes in environmental amenities. These measures should be helpful in determining costs and benefits of different environmental policies.

2.1 Data problems

The question that the analyst must confront is given observations on choices made by individuals and the price paid, how can the imputed price of a product for which a well defined measure does not exist, be measured. So the first issue to resolve is how to measure amenities, and what are the general data requirements to fulfill that task. In the literature of valuing marginal amenities changes in the framework of hedonic models it has been long recognized that there is no unique measure for a particular amenity. Instead several measures of the same amenity are available in many cases. This issue has been raised by different authors. For instance, Bartik and Smith (1987), Smith (1990), and Russell and Smith (1990). The last one mentioned makes explicit reference to issues relevant for cost-benefit analysis of environmental policies.

2.2 Estimation problems

Cropper and Oates (1992) describe some of the problems in estimation the "value of improved environmental amenities." They discuss the following general methods: (1) Indirect market methods, and (2) Contingent valuation. Indirect market methods are based on choices made by individuals. Hedonic methods belong to this category.

The major problem facing estimation of implicit values is that the use of proxies for amenities produces biased and inconsistent estimates. And while this has been recognized in the literature, not much has been done to remedy this. The next subsection addresses this problem.

Hedonic estimations focus on the individual's marginal values or implicit prices on characteristics of houses. Discrete choice models estimate the probability that a house with specific characteristics be purchased. The hedonic method consists of estimating a price function, i.e., regress observed prices p of different houses on the characteristics z of those houses. This is done by estimating an equation like

$$p = f(z) + \epsilon \tag{2.1}$$

where ϵ is an error term independent of z. Marginal prices of each characteristic from the estimated hedonic price function are then calculated. In order to estimate implicit prices for different amenities, researchers usually include "proxy" variables for the amenities that they are interested in estimating.

The simple errors–in–variables model may be represented by

$$y_i = \beta_0 + \beta_1 x_i^* + u_i \qquad i = 1, \ldots, n \tag{2.2}$$

$$x_i = x_i^* + \epsilon_i \tag{2.3}$$

where x_i^* is the variable measured with error. The model can be rewritten as

$$y_i = \beta_0 + \beta_1(x_i - \epsilon_i) + u_i = \beta_0 + \beta_1 x_i + (u_i - \beta_1 \epsilon_i) = \beta_0 + \beta_1 x_i + v_i$$

where now x_i and v_i are correlated.

The application of maximum likelihood methods or ordinary least squares methods to estimate a model like this leads to biased and inconsistent parameter estimates. Alternative methods include instrumental variables (IV) [e.g., Bowden and Turkington (1984)] and latent variables [e.g., Aigner et al. (1984)]. In order to get unbiased and consistent estimates of

implicit prices on housing characteristics a method based on the existence of multiple indicators is applied in this paper. Since neighborhood quality (and amenities in general) cannot be precisely measured by a proxy variable, but there are indicators available, one method to get consistent estimates is by using a latent–variable model. The variable "neighborhood quality" becomes then a latent–variable (an unobserved "true" variable) for which indicators are available. Section 4.3 addresses the method to estimate this type of models.

3 Theoretical framework

The theoretical model presented here is a modified version of Gorman (1956,1980), Lancaster (1966), Rosen (1974), and Pudney (1981).[1]

Let the K different houses traded in the market be denoted by $X_1, X_2, ..., X_K$, and let $Z_1, Z_2, ..., Z_n$ be the n different homogeneous characteristics (or attributes). We use $x = (x_1, ..., x_K)$ and $z = (z_1, ..., z_n)$ to denote the quantities of goods and characteristics consumed. Since one of the primary motivations for the characteristics approach is to simplify complex market structures, where many differentiated products interact, to a smaller number of homogeneous attributes, we shall restrict our attention to the case where $K > n$. It is assumed a preference structure

$$U = U\left[z^*; \varphi(x)\right] \tag{3.1}$$

which is a function of both observable and unobservable characteristics z^*, and unobserved specific effects of goods x (a specific value attached to particular houses, unrelated to their characteristics). The utility function U is assumed to be strictly quasi-concave.

We assume that the relationship between z^* and x is linear,

$$z^* = B^* x \tag{3.2}$$

where $B = (b_{ij})$ is an $n \times K$ matrix with some known elements. Let p be the $(K \times 1)$ vector of the unit prices of X. An individual consumer, h, is assumed to face a budget constraint,

$$p'x = m^h \tag{3.3}$$

[1] Following Arguea and Hsiao (1993).

Maximizing utility (3.1) subject to the budget constraint (3.3) gives the marginal condition for the hth consumer:

$$p_j \geq \sum_{i=1}^{n} \left(\frac{1}{\lambda}\frac{\partial U}{\partial z_i}\right) b_{ij} + \sum_{\ell=1}^{q} \left(\frac{1}{\lambda}\frac{\partial U}{\partial \varphi_\ell}\right) \frac{\partial \varphi_\ell}{\partial x_j}, \tag{3.4}$$

where q denotes the number of good specific effects and λ^h is the Lagrangian multiplier. The Lagrangian multiplier λ^h can be viewed as the marginal utility of money for the hth consumer. Hence $\frac{1}{\lambda}\frac{\partial U}{\partial z_i}$ and $\frac{1}{\lambda}\frac{\partial U}{\partial \varphi_\ell}$ may be viewed as the shadow prices of the characteristics z_i (p_{z_i}), and the specific effects φ_ℓ, $p_{\varphi_{h\ell}}$. Thus, at the optimum the following set of equations should be satisfied:

$$p_j \geq \sum_{i=1}^{n} p_{z_{h_i}} b_{ij} + \sum_{\ell=1}^{q} p_{\varphi_{h\ell}} \frac{\partial \varphi_\ell}{\partial x_j}, \tag{3.5}$$

where the equality sign holds for all goods the consumer actually consumes, or is on the verge of consuming. Equation (3.5) represents a hedonic function. This equation gives form to the general price function as presented in equation (2.1), and it is the theoretical basis for the empirical estimation of marginal prices that takes place in Section 5.

4 Alternative estimation methods

Typically, hedonic functions have been estimated using least square methods. As pointed out in Section 2.2, instrumental variable estimators provide unbiased and consistent estimators when we are in the presence of stochastic regressors. A proxy variable is a partial solution Wickens (1972) and McCallum (1972) showed that it always pays to include a proxy, since there a smaller asymptotic bias, when a proxy is included, compared when the variable is ignored.

Estimation of (2.1) has been carried out using either ordinary least squares without a proxy or with a proxy for neighborhood quality. There are also studies that address the issue of functional form. Here, we will follow the result from the theoretical model in Section 3 and assume that $f(z)$ is linear, without attempting to test different functional forms.

The linear form of $f(z)$, its least square solution and the covariance matrix are in matrix notation

$$p = Z\beta + \epsilon \tag{4.1}$$

$$\beta = (Z'Z)^{-1}Z'p \tag{4.2}$$

$$\mathrm{Var}(\hat{\beta}) = \sigma^2(Z'Z)^{-1} \tag{4.3}$$

where Z is the matrix of order k that includes measures of housing characteristics, unit quality, equipment, and may include a proxy for neighborhood quality. These proxies usually include racial composition of neighborhood, public services available, income distribution, and crime rate.

As it was shown in Section 3, biased and inconsistent estimates are obtained if least square or even maximum likelihood methods are used. The availability of different indicators for neighborhood quality suggests the use of instrumental variables. Let W be the matrix of instruments of order $[(n+q)\times 1]$. The two possible estimates of β depend on the condition $q \geq k$. The $q = k$ and the $q > k$ case, together with the asymptotic covariance matrix follow

$$\tilde{\beta} = (W'Z)^{-1}W'p \tag{4.4}$$

$$\tilde{\beta} = \left[Z'W(W'W)^{-1}W'Z\right]^{-1} Z'W(W'W)^{-1}W'p \tag{4.5}$$

$$\mathrm{Avar}(\tilde{\beta}) = \sigma^2 \left[Z'W(W'W)^{-1}W'Z\right]^{-1} \tag{4.6}$$

When additional information is available in the form of an indicator IV estimates are superior to OLS. The estimators shown above apply to the case of spherical error terms.[2] The next model is an alternative to IV when several indicators are available, although IV estimates provide good initialization values.

Finally, there is a family of models specially useful to handle latent variable structures. These models have been designed to estimate causal structures among latent variables for which indicators are observed and available. Thus, the case of measurement errors in some of the independent variables constitutes a particular case. The estimation is based on maximum likelihood methods. One of the most widely used methods is the linear structural equation formulation of Jöreskog (1973). Other models in the literature to handle latent–variable structures include, for instance, partial least squares as in Wold (1982), or models by Bentler and Weeks (1980), or McDonald (1978). The argument of the paper is that given that additional

[2] Nonspherical disturbances instrumental variable estimators are discussed in detail in Bowden and Turkington (1984).

information is available in the form of a number of indicators, there is a potential gain in efficiency when these indicators are incorporated in the estimation. A model of this type is estimated in Section 5. It follows the notation popularized by Jöreskog (1977).[3]

5 Application: AHS data

5.1 Data description

This study was carried out using data from the American Housing Survey (AHS). This survey is conducted by the U.S. Department of Commerce – Bureau of the Census for the Department of Housing and Urban Development (HUD). The survey is conducted annually for different Metropolitan Statistical Areas (MSA) and contains data on general housing characteristics, equipment, housing quality, housing expenses, neighborhood conditions, and demographic information. These data are widely used in the estimation of models involving housing characteristics.

In this paper I included four MSA's from the southeast region of the U.S. They are (with the year of the survey in parenthesis): Tampa (1985), Miami (1986), New Orleans (1986), and Atlanta (1987). This constitutes the first of a series of studies on the behavior of the U.S. housing market, and the southeast was chosen as the starting point.[4] Data used for the estimation was limited to single-family, owner occupied houses. A total of 808 observations were used in the estimation. Table 1 lists variables, their definition, and summary statistics.

The criteria to select the variables to analyze included availability of data so that some measure of general housing characteristics, equipment, and neighborhood quality was present. Also I tried to include variables used in similar studies for comparison purposes. Finally, attention was paid to the independence of variables. The selected representative group had to pass a test based on the use of collinearity measures. This was done using the method suggested by Belsley, Kuh, and Welsch (1980) based on condition indices. These indices are computed based on the singular values of the data matrix (Z). Based on these indices the following variables were selected: square footage of the unit (UNITSF), number of rooms (ROOMS),

[3]The interested reader is also referred to Jöreskog and Sörbom (1988) for further details.

[4]The sponsors of this study at the University of West Florida, Pensacola, Florida, where this research has taken place, have shown special interest in this region.

number of baths (NBATHS); 0–1 variables that indicate whether the characteristic is present (= 1), or not (= 0). These characteristics are: Central air conditioning (AIRCONDS), working fire place (FPLWKD), porch (PORCHD), and garage (GARAGED). The variable ROOMS measures the number of rooms excluded the bathrooms. For instance, a two thousand-square foot house might easily contain 6-8 rooms (e.g., 3 bedrooms, living room, dining room, family room, kitchen, and laundry room). Finally, the following indicators (0–1 variables) for neighborhood quality were included: if there is some junk in neighborhood (NEJUNK), if crime in neighborhood is bothersome (NCRIME), if noise in neighborhood is bothersome (NNOISE), if litter or housing deterioration is bothersome (NLITTER), if respondent is either black, american indian or hispanic (NWHITE), and if respondent finished a four-year college education (SCHCOLL).

In addition, dummy variables for each city where defined in order to capture differences in expected prices, and marginal contribution to prices from changes in square footage. The four variables that finally remained in the model were TAMPA, MIAMI, and their interactions with square footage, USFT, and USFM, respectively.

The dependent variable in studies of this sort is the price of the property. But properties have market values that are not observed. Earlier, Robins and West (1977) have recognized the presence of errors of measurement in property values in a framework similar to this one. Errors of measurement occur not only in right-hand side variables but also in left-hand side variables. This paper extend that idea incorporating not only measurement errors in the price variable, but also in housing characteristics. The AHS presents two measures of the value of the house. Both the transaction price and the owners opinion on the actual value of the house are reported.

In this study I incorporate in the estimation the natural logarithm of both (LPK, and LVALUE, respectively), recognizing the fact that both are imperfect measures for the actual value of the house. Therefore, both are used as indicators for a variable that represents the market value of the house that is actually not observed (MKTVALUE). The results will allow to analyze the relative accuracy of market values using these two measures.

5.2 Empirical model

In the context of the application to the housing market the structural and measurement models shown in equations (4.7)–(4.9) can be simplified for this particular case. The structural model can be written as

$$\eta_i = \gamma'\xi_i + \zeta_i \qquad (5.1)$$

where η_i is the unobserved market value of the i-th house in the sample, ξ is the $n \times 1$ vector of explanatory variables, and γ is the $n \times 1$ vector of parameters to estimate. The model is already in reduced form. It is assumed that except for neighborhood quality, all other explanatory variables are measured without error. Equation (5.1) is the empirical implementation of the theoretical model presented in Section 3, and represented by equation (3.5). Two indicators for the actual market value of the property are available: the transaction price and the owner's opinion about the actual value of the house. The measurement model for η becomes

$$y = \lambda_y \eta + \epsilon \qquad (5.2)$$

where y and λ_y are 2×1 vectors. For the exogenous variables the measurement model is

$$x = \Lambda_x \xi + \delta \qquad (5.3)$$

The model is completely specified when restrictions are imposed upon the parameter matrices. This is the process of identification. The parameter matrices in the present model are defined in what follows. There are 11 variables measured without error and two latent variable, one exogenous (NQUALITY), and one endogenous (MKTVALUE). There are 6 available indicators for the exogenous latent, and 2 indicators for the endogenous latent. Hence, x is of order 17×1, Λ_x is 17×12 and ξ is a 12×1 vector. Restrictions are applied to Λ_y, Λ_x, Θ_ϵ, and Θ_δ. By normalization of both set of variables in y and x, the scale of the latent variables is defined. Thus, those parameters are set equal to one. In the case of the dependent latent (MKTVALUE) the log of the transaction price (LPK) was used as the scale variable. In the case of neighborhood quality (NQUALITY), the scale was defined by the indicator of education of head of household (SCHCOLL). The γ's for the other 5 indicators are set free. There is one parameter estimated in the Λ_y matrix, 5 parameters in the Λ_x matrix, 12 parameters in the Γ matrix, 78 parameters in the Φ (the covariance matrix of ξ) matrix, one parameter in Ψ (the variance of the error term in the structural model), and, finally, there are 3 and 21 parameters in matrices Θ_ϵ and Θ_δ, the covariance matrices of the error terms in the indicator equations for y, and x, respectively.

5.3 Results

Table 1 contains descriptive statistics including individual indices of kurtosis. The table also shows Mardia's normalized multivariate index of kurtosis.[5] These indices give an indication of the degree of departure from normality, which in this case is clear, and it is mostly explained by the presence of binary variables. The sample correlation matrix is included in Table 2.

Least-square (OLS) estimates with no proxy, one proxy, and instrumental-variable (IV) estimates are included in Table 3. These results are included for comparison purposes. Fit indices for alternative models are presented in Table 4. Results on the structural and measurement models (5.1)-(5.3) are presented in Tables 5 and 6.[6] Multiple correlations together with error variances and covariances of exogenous variables are shown in Tables 7 through 9.

The model presented in Section 5.2 is estimated using maximum likelihood under normality. Standard assumptions on this model are presented in Appendix I. The discussion that follows focuses on the potential problems when nonnormal multivariate data are used, and the approach followed in this paper regarding this issue. The inclusion of categorical variables has consequences with respect to model fit , making the validity of some tests doubtful in the presence of high levels of kurtosis. This occurs here with some variables, in particular binary variables that measure the quality of neighborhoods, and even though univariate non-normality does not necessarily imply multivariate non-normality, it may be a cause. The literature on structural equation models has offered several approaches to solve some of the problems generated by non-normality. At the same time, there is a body of work showing evidence that even under nonnormality, the tests are asymptotically valid assuming that the latent variables are independently distributed.[7] The approaches dealing with non-normality include data transformations, rescaling of test statistics, and estimation methods that are distribution free.[8] The third approach has not been widely accepted in the literature of structural equation models. Muthén and Kaplan (1992) show that asymptotically distribution free (ADF) methods do not perform well in large model and large samples. Inflated Chi-squared values and downward biased standard errors are two important results from their Monte Carlo studies. They also show that maximum likelihood estimates based on normality show very little bias

[5] Mardia's index is asymptotically distributed as a normal variate with mean $p(p+2)$ and variance $8p(p+2)/n$, where p refers to the number of variables in the covariance matrix to analyze and n refers to the number of observations (19 and 808, respectively).

[6] Maximum likelihood estimates were obtained using PROC CALIS from SAS Institute Inc. (1989).

[7] Some of the references include Browne (1987), Browne and Shapiro (1988), and Amemiya and Anderson (1990).

[8] Bollen (1989) has proposed the use of nonparametric tests.

even under nonnormal conditions.[9] The treatment of the normality issue in this paper has followed two routes, and it is a mix of the first two above mentioned approaches. First, using the Mahalanobis measure for multivariate normality, those observations with large measures were eliminated. The removal of outliers produces the same effects in terms of results as some robust methods.[10] Also, binary variables with mean values of less than 0.08 were disregarded as viable indicators. This basically occurs when only a few of the respondents indicate that the attribute is present.[11] Second, given the lack of consensus about the effectiveness of distribution free methods, I have adopted the approach of correcting the values of the Chi-squared test statistic.[12]

All the analysis was carried out using information from all four MSA's described in Section 5.1. Prices were adjusted to 1986 values. Dummy variables for Tampa, Miami, and Atlanta were included to control for differences in means with New Orleans as the reference group. Tests on the dummy for Atlanta and its interaction with square footage resulted in no significant difference between marginal effects for that city and New Orleans. Therefore, in subsequent analysis the reference group includes both cities Atlanta and New Orleans.

Results in Table 3 show that all the coefficients are significant (at the 1% level, unless stated otherwise), and show the expected sign. OLS with a proxy is superior than the no-proxy case. Not only the precision of the estimates is higher but the variance of the model is lower. Parameters estimates are fairly stable across models, except for the estimate of neighborhood quality that is not significant at low levels (with a p-value of 0.11) in the IV model. The precision of the parameters is also high in the proxy model. Conditional on the set of characteristics, and based on the sample information prices on average are higher in Miami and lower in Tampa compared with houses of the same characteristics in Atlanta and New Orleans. However, the marginal effect of additional square footage is positive for Tampa and New Orleans. This indicates that additional size is relatively more expensive in these two cities compared with Miami and Atlanta.

Several proxies for neighborhood quality were utilized in the least squares results. These included each of the six indicators available. SCHCOLL, and NNOISE were significant and showed the expected sign (positive and negative, respectively). A variable for racial composition was also tested as suggested by Li and Brown (1980) and Dubin and Sung (1990). This

[9]More recently, West, Finch, and Curran (1995) have provided a summary of current empirical work under non-normality conditions, where similar conclusions are reached regarding ADF methods.

[10]See, for instance, Gallini and Casteel (1987).

[11]However, there is no way to distinguish between a zero response when the characteristic is not present, and a zero response when the individual is not well informed about the characteristic in question.

[12]Satorra and Bentler (1988) have proposed such correction.

and the other three indicators were not significant at standard 5% levels. Even though the introduction of a proxy is better than no proxy at all, estimates are still biased and inconsistent due to the stochastic nature of the proxies. The inclusion of a proxy variable results in a persistent bias of the estimated coefficient towards zero. Thus, trying to capture neighborhood effects through variables with errors of measurement underestimates the marginal effect of neighborhood quality. This is the main message of the paper. In order to verify this, a test for measurement error was performed in each case. The test is based on a statistic suggested by Durbin (1954).[13] This test is distributed χ^2_m, where m is the number of suspected stochastic variables. Large values of the test reject the hypothesis of independence. In all cases that hypothesis was easily rejected, suggesting that the regressor used as a proxy is stochastic.

Tables 4, 5 and 6 show summary fit indices for alternative models and the estimates of the structural equations model presented in equations (5.1)-(5.3), using maximum likelihood methods.

There is some controversy about the accuracy of fit indices. Some of the drawbacks summarized and discussed in Gerbing and Anderson (1993), and Hu and Bentler (1995), point to the selection of indices that include some correction for sample size or number of estimated parameters. Following the recommendation found in recent literature, I have included the following indices: Akaike's Information Criterion (AIC), McDonald's (1989) centrality index, and Bollen's (1989) Delta2 index. The indices are used for comparison and selection of models, rather than as a stand alone unit of goodness of fit. The validity of alternative models was tested using likelihood ratio (LR) tests. Given that the main latent structure occurs in the variable NQUALITY, tests where performed by imposing restrictions on the error covariance matrix of the measurement equations for that variable. Due to the multivariate non-normality nature of the data I corrected the LR tests using the inverse of Mardia's coefficient of relative kurtosis as the corrective factor, as suggested by Browne (1984). However, results from tests do not change with this correction.

Different models resulting from alternative hypotheses about error covariances were estimated and a summary with fit indices of the relevant models is included in Table 4. Model C, the most restricted model, was easily rejected. Further imposing zero restrictions on Θ_δ, and using likelihood ratio tests, lead to the final Model E, where three covariances are free (NEJUNK-NLITTER, SCHCOLL-NLITTER, and SCHCOLL-NLITTER), and with two equality con-

[13]It has the following form $Q = (\tilde{\beta} - \hat{\beta})' \left\{ \tilde{\sigma}^2_u \left[Z'W(W'W)^{-1}W'Z \right]^{-1} - \hat{\sigma}^2_u (Z'Z)^{-1} \right\}^{-1} (\tilde{\beta} - \hat{\beta})$ where $\tilde{\beta}$ is the IV estimator, $\hat{\beta}$ is the LS estimator and $\tilde{\sigma}^2_u$, $\hat{\sigma}^2_u$ are the IV, and LS estimates of the residual variances, respectively.

straints among variances (NCRIME, NNOISE, and NLITTER). This was the model with the lowest AIC value. Except for the clearly inferior Model C, the centrality and Delta2 indices do not help to differentiate among the alternative models. Model E fits the data comparatively well based on different indices presented in Table 6. This model also has the property that the parameters can be given a reasonable interpretation, consistent with what is expected in this type of hedonic models.

The following results refer to the specification of Model E. Table 5 shows the parameters of the structural model (γ's). Table 6 shows the estimated portion of the Λ_x matrix, and the estimate of λ_y. The key parameter of interest is the estimate for neighborhood quality which is positive and significant. An attempt to provide an interpretation of that coefficient is made. It seems that prices in a better neighborhood are expected to be on average a 65% higher, approximately.[14] All the coefficients are significant (as in the other previous models). There is some variation in the size of the coefficients, especially in AIRCONDS, ROOMS, GARAGED, and MIAMI. Every variable was defined to represent positive marginal valuations and that is the sign obtained in every case. Compared with the OLS–proxy case the value of the NQUALITY coefficient is higher in the structural model. This result is consistent with the negative asymptotic bias in OLS estimation.

The estimates for Λ_x show the significance of the indicators chosen to reflect quality of neighborhood. Judging by the high t–values, every indicator chosen is strongly associated with the latent independent variable. The signs are consistent with the definition of the indicators. The strongest association occurs with the existence of some junk in neighborhood (NEJUNK). Unlike in the previous models, racial composition (NWHITE) as measured by the indicator of a non-white owner, shows a high negative association with NQUALITY. Table 7, containing squared multiple correlations, clearly indicates that the highest correlations appear in these two variables. For the dependent latent variable the statistical significance of the owner's opinion on the value of the house (LVALUE) is very high. The coefficient is very close to one (0.96) which indicates that both represent a similar measure of market value. However, the transaction price exhibits a smaller variance, resulting in a higher correlation coefficient (0.80 against 0.74 in Table 7).

Table 8 shows the variances of exogenous variables. Without imposing any restrictions on the sign, all variances are positive. Finally, Table 9 presents the estimated correlations among exogenous variables, including the latent NQUALITY.

[14]Given that the scale of this latent variable is associated with owner's level of education which is a binary variable, the interpretation of this coefficient is limited to the case where only two qualities of neighborhoods are identified.

6 Final Comments

I have presented a model that allows the estimation of hedonic price functions when nonobservables are present. The contribution is methodological and it is focused on studies in the area of real estate. It is shown that the use of indicators (even though they are categorical variables) provide a useful way to estimate neighborhood effects applying a systematic treatment of not only the error of measurement in prices, but also by considering the variable "neighborhood quality" a latent construct.

The estimates presented are unbiased and consistent. The method consists of an application of the errors–in–variables approach when more than one instrument is available. The model presented was applied to the housing market and it represents an illustration of the methodology. Results illustrate the use of variables that capture quality of neighborhood to help explain the effect of neighborhood quality on housing prices. The results shown are consistent with findings in other papers like Dubin and Sung (1990) and Palmquist (1984). However, their results for the proxies are biased and inconsistent.

Strong positive effects of education of households with neighborhood quality is observed. At the same time additional indicators for crime in area, junk, noise, litter, and non white population are strongly negatively linked with quality of neighborhood. The effect of neighborhood quality on prices is estimated with good precision.

The results confirm that the usual estimates of marginal effects of improvement in neighborhood quality on housing values are underestimated with OLS methods, when a proxy is included. Even when IV estimates are consistent, the methodology used here incorporates errors of measurement in the estimation allowing to capture a richer interaction among the indicators through the estimation of the error covariance matrix. The conclusions regarding underestimating effects can be extended to evaluate the contribution to property values of general improvements in environmental amenities. This suggest that the method can be useful in a more general framework where several unobserved amenities are included in the model and when several indicators are available, even when they are binary variables.

A possible extension to this study includes expanding the data set in two directions. First, using panel data, and second incorporating other regions. This would allow to address questions on reasons for price shifts across regions, and over time.

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Appendix I
Maximum likelihood

The full model is formalized by a system of structural relations among the true variables that are unmeasured, referred as the structural model, and by a measurement model. The structural model is:

$$\eta = B\eta + \Gamma\xi + \zeta \tag{A.1}$$

where η and ξ represent the $m \times 1$ and $n \times 1$ vectors of latent variables, respectively. B and Γ are coefficient matrices of order $m \times m$ and $m \times n$, respectively, and ζ is an $m \times 1$ error term. The structural model is completed with the measurement model that establishes the link between the unobserved and observed variables.
The measurement model for η is

$$y = \Lambda_y \eta + \epsilon \tag{A.2}$$

where y is the $p \times 1$ vector of indicators for η, ϵ is a $p \times 1$ vector of measurement errors and Λ_y represents the $p \times m$ matrix of coefficients. A similar model holds for ξ

$$x = \Lambda_x \xi + \delta \tag{A.3}$$

where x and δ are the $q \times 1$ vectors of indicators for ξ and measurement error, respectively, and Λ_x is a coefficient matrix of order $q \times n$. The following conditions are assumed to hold

$$E(\zeta\xi) = E(\epsilon\eta) = E(\delta\xi) = E(\zeta\epsilon) = E(\zeta\delta) = E(\epsilon\delta) = 0$$

$$E(\eta) = E(\xi) = E(\zeta) = 0$$

The model represented by equation (4.7) can be interpreted as a simultaneous equation system. In regression models η and ξ are assumed to be measured without error. In structural equation models there is an explicit measurement model that captures the errors of measurement when indicators for the true variables are used. The parameters to estimate are those in the measurement model matrices Λ_y, Λ_x, in the structural model, B, and Γ, and those in the covariance matrices. The four covariance matrices Φ, Ψ, Θ_ϵ, and Θ_δ, correspond to the random variables ξ, ζ, ϵ, and δ, respectively.
Estimation is carried out by analyzing the covariance structure associted to the model. Define Σ as the population covariance matrix of the vector $z = (y', x')'$, and let θ be the vector of parameters to estimate. Then parameters are estimated so that the estimated covariance matrix

$$\hat{\Sigma} = \Sigma(\hat{\theta})$$

is close to the matrix S of second sample moments of y and x, where $\hat{\theta}$ denotes the estimated values of θ. Hence a small difference $S - \hat{\Sigma}$ should be expected if the model is true. Maximum likelihood estimates are obtained by minimizing[15]

$$F = \ln|\Sigma(\theta)| + \mathrm{tr}\left[S\Sigma^{-1}(\theta)\right] - \ln|S| - (p+q) \tag{A.4}$$

which approaches to zero as $\hat{\Sigma}$ approaches to S.

[15]See Bollen (1989) for a derivation. Two well known programs that estimate latent-variable models are EQS and LISREL. SAS (Statistical Analysis System), Version 6.07 has a procedure to estimate this type of models called CALIS

Table 1
Definition of Variables and Descriptive statistics
N = 808

Definition	Variable Name	Mean	Standard Deviation	Kurtosis
Purchase price of house and lot (log)	LPK	10.944	0.6576	3.6262
Property value (sample unit only) (log)	LVALUE	11.133	0.6822	5.0647
Dummy variable, 1 if house in Tampa	TAMPA	0.285	0.4521	-1.1012
Dummy variable, 1 if house in Miami	MIAMI	0.158	0.3653	1.5175
Unit size in 000 square feet	UNITSF	1.704	0.7524	1.7309
Garage/carport present	GARAGED	0.672	0.4697	-1.4645
Number of rooms in house	ROOMS	6.097	1.5509	0.6418
Number of bathrooms	NBATHS	1.782	0.5737	1.3240
Fire place working	FPLWKD	0.407	0.4916	-1.8613
Porch present	PORCHD	0.886	0.3178	3.9428
Central air conditioning system	AIRCONDS	0.820	0.3839	0.8034
Some junk in neighborhood	NEJUNK	0.243	0.4296	-0.5721
Crime in neighborhood is bothersome	NCRIME	0.086	0.2814	6.6864
Noise in neighborhood is bothersome	NNOISE	0.105	0.3069	4.6596
Litter or housing deter. bothersome	NLITTER	0.158	0.3653	1.5175
Owner black/am indian/asian/hispanic	NWHITE	0.116	0.3208	3.7580
4-year College completed	SCHCOLL	0.200	0.4006	0.2473
Interaction term: UNITSF*TAMPA	USFT	0.407	0.7027	1.1887
Interaction term: UNITSF*NEW ORLEANS	USFN	0.345	0.7384	3.8275

Normalized Mardia's multivariate kurtosis: 42.8
Relative multivariate kurtosis: 1.2131

Table 2
Sample correlation matrix

VARIABLE*	LPK	LVALUE	TAMPA	MIAMI	UNITSF	GARAGED	ROOMS	NBATHS	FPLWKD	PORCHD
LPK	1.000	0.767	-0.237	0.087	0.502	0.295	0.461	0.499	0.357	0.276
LVALUE	0.767	1.000	-0.203	0.051	0.535	0.302	0.496	0.442	0.372	0.282
TAMPA	-0.237	-0.203	1.000	-0.275	-0.235	0.139	-0.174	-0.180	-0.234	-0.144
MIAMI	0.087	0.051	-0.275	1.000	-0.071	-0.195	-0.148	-0.001	-0.291	-0.026
UNITSF	0.502	0.535	-0.235	-0.071	1.000	0.250	0.649	0.471	0.403	0.221
GARAGED	0.295	0.302	0.139	-0.195	0.250	1.000	0.253	0.190	0.236	0.173
ROOMS	0.461	0.496	-0.174	-0.148	0.649	0.253	1.000	0.495	0.417	0.138
NBATHS	0.499	0.442	-0.180	-0.001	0.471	0.190	0.495	1.000	0.381	0.217
FPLWKD	0.357	0.372	-0.234	-0.291	0.403	0.236	0.417	0.381	1.000	0.218
PORCHD	0.276	0.282	-0.144	-0.026	0.221	0.173	0.138	0.217	0.218	1.000
AIRCONDS	0.381	0.284	-0.054	-0.071	0.241	0.140	0.173	0.413	0.237	0.137
NEJUNK	-0.232	-0.236	0.055	-0.049	-0.222	-0.199	-0.125	-0.222	-0.183	-0.114
NCRIME	-0.032	0.032	-0.097	0.059	0.016	-0.094	0.006	-0.052	-0.013	0.055
NNOISE	-0.108	-0.082	-0.003	0.072	-0.068	-0.010	-0.040	-0.025	-0.038	0.021
NLITTER	-0.012	-0.026	-0.042	0.044	-0.004	-0.029	-0.027	-0.072	-0.097	-0.026
NWHITE	-0.123	-0.074	-0.127	0.170	-0.116	-0.158	-0.020	-0.105	-0.175	-0.064
SCHCOLL	0.214	0.218	-0.105	0.011	0.167	0.067	0.146	0.152	0.208	0.092
USFT	-0.076	-0.044	0.917	-0.252	-0.067	0.177	-0.039	-0.045	-0.133	-0.068
USFN	0.116	0.069	-0.297	-0.203	0.134	-0.110	0.141	0.052	-0.020	0.006

Table 2 (cont.)
Sample correlation matrix

VARIABLE*	AIRCONDS	NEJUNK	NCRIME	NNOISE	NLITTER	NWHITE	SCHCOLL	USFT	USFN
LPK	0.381	-0.232	-0.032	-0.108	-0.012	-0.123	0.214	-0.076	0.116
LVALUE	0.284	-0.236	0.032	-0.082	-0.026	-0.074	0.218	-0.044	0.069
TAMPA	-0.054	0.055	-0.097	-0.003	-0.042	-0.127	-0.105	0.917	-0.297
MIAMI	-0.071	-0.049	0.059	0.072	0.044	0.170	0.011	-0.252	-0.203
UNITSF	0.241	-0.222	0.016	-0.068	-0.004	-0.116	0.167	-0.067	0.134
GARAGED	0.140	-0.199	-0.094	-0.010	-0.029	-0.158	0.067	0.177	-0.110
ROOMS	0.173	-0.125	0.006	-0.040	-0.027	-0.020	0.146	-0.039	0.141
NBATHS	0.413	-0.222	-0.052	-0.025	-0.072	-0.105	0.152	-0.045	0.052
FPLWKD	0.237	-0.183	-0.013	-0.038	-0.097	-0.175	0.208	-0.133	-0.020
PORCHD	0.137	-0.114	0.055	0.021	-0.026	-0.064	0.092	-0.068	0.006
AIRCONDS	1.000	-0.200	-0.131	-0.123	-0.018	-0.233	0.138	0.037	0.049
NEJUNK	-0.200	1.000	0.040	0.003	0.196	0.225	-0.119	-0.000	0.093
NCRIME	-0.131	0.040	1.000	0.038	-0.025	0.108	0.022	-0.090	0.100
NNOISE	-0.123	0.003	0.038	1.000	-0.027	0.064	-0.021	-0.023	-0.064
NLITTER	-0.018	0.196	-0.025	-0.027	1.000	0.086	0.079	-0.042	0.019
NWHITE	-0.233	0.225	0.108	0.064	0.086	1.000	-0.018	-0.121	0.023
SCHCOLL	0.138	-0.119	0.022	-0.021	0.079	-0.018	1.000	-0.059	0.006
USFT	0.037	-0.000	-0.090	-0.023	-0.042	-0.121	-0.059	1.000	-0.272
USFN	0.049	0.093	0.100	-0.064	0.019	0.023	0.006	-0.272	1.000

*For definitions of variables refer to Table 1.

Table 3
Hedonic Price Function
Ordinary Least Squares and Instrumental Variables Estimates

Variable	OLS–No proxy Estimate (t-value)	OLS–Proxy Estimate (t-value)	Inst. Variable Estimate (t-value)
UNITSF	0.1198 (3.74)	0.1168 (3.65)	0.1071 (3.08)
AIRCONDS	0.3098 (6.29)	0.3012 (6.12)	0.2737 (4.66)
ROOMS	0.0575 (3.71)	0.0568 (3.68)	0.0545 (3.37)
FPLWKD	0.1571 (3.53)	0.1430 (3.19)	0.0979[a] (1.48)
PORCHD	0.1986 (3.52)	0.1951 (3.47)	0.1841 (3.10)
GARAGED	0.2429 (6.13)	0.2422 (6.13)	0.2397 (5.83)
NBATHS	0.1676 (4.37)	0.1669 (4.36)	0.1645 (4.14)
TAMPA	-0.4435 (-3.95)	-0.4394 (-3.93)	-0.4264 (-3.65)
MIAMI	0.3871 (6.76)	0.3792 (6.64)	0.3539 (5.44)
USFT	0.2768 (4.13)	0.2756 (4.12)	0.2715 (3.90)
USFN	0.1039 (3.92)	0.1038 (3.93)	0.1036 (3.78)
SCHCOLL		0.1085 (2.49)	0.4554[b] (1.24)
$\bar{R}^2$	0.475	0.479	0.428
SSE	183.3	181.8	196.4
N	808	808	808

[a]P-value=0.07. [b]P-value=0.11.

Table 4
Model Fit Indices

Model:[a] Θ_ϵ, Θ_δ	AIC[b]	CI[c]	Delta2[d]	χ^2	DF
A: free, free	48.95	0.9296	0.9773	186.95	69
B: diag, free	46.95	0.9302	0.9775	186.95	70
C: diag, diag	73.04	0.9068	0.9695	243.04	85
D: diag, (1)	37.90	0.9285	0.9769	201.90	82
E: diag, (2)	33.94	0.9296	0.9772	201.94	84
F: free, (2)	35.94	0.9290	0.9771	201.94	83

[a]Θ_ϵ, and Θ_δ are the covariance matrices of measurement errors across indicators for "market value", and "neigborhood quality," respectively. (1), and (2) indicate restrictions on Θ_δ. (1) indicates that only three covariances are free (NJUNK-NLITTER, SCHCOLL-NLITTER, and NWHITE-SCHCOLL), and (2) like in Model D with two equality constraints (NCRIME, NNOISE, and NLITTER).
[b]Akaike (1987) Information Criterion.
[c]McDonald (1989) Centrality Index.
[d]Bollen (1988).

Table 5
Hedonic Price Function
Maximum Likelihood Estimates
Structural Model

Parameters	Variable	Estimate (t-value)	Standardized Coefficients
γ_1	UNITSF	0.1142 (2.83)	0.1276
γ_2	AIRCONDS	0.0788 (2.09)	0.0881
γ_3	ROOMS	0.1952 (5.18)	0.2181
γ_4	FPLWKD	0.0705 (1.85)	0.0787
γ_5	PORCHD	0.1009 (3.90)	0.1127
γ_6	GARAGED	0.1354 (4.47)	0.1513
γ_7	NBATHS	0.1020 (3.14)	0.1139
γ_8	TAMPA	-0.3589 (-4.71)	-0.4009
γ_9	MIAMI	0.1990 (6.57)	0.2223
γ_{10}	USFT	0.3340 (4.84)	0.3731
γ_{11}	USFN	0.1056 (3.70)	0.1179
γ_{12}	NQUALITY	0.6508 (2.33)	0.2044

Table 6
Hedonic Price Function
Maximum Likelihood Estimates
Measurement Model

Parameters	Variable	Estimate (t-value)	Standardized Coefficients
λ_2	LVALUE	0.9577 (28.09)	0.8573
λ_{12}	NEJUNK	-1.5734 (-5.27)	-0.4425
λ_{13}	NCRIME	- 0.5508 (-3.05)	-0.1543
λ_{14}	NNOISE	-0.4322 (-2.52)	-0.1216
λ_{15}	NLITTER	-0.3743 (-2.07)	-0.1056
λ_{16}	NWHITE	- 1.6470 (-5.18)	-0.4631

Table 7
Squared Multiple Correlations

Variable	Error Variance	Total Variance	R^2
LPK	0.1988	0.9999	0.8011
LVALUE	0.2651	0.9999	0.7348
NEJUNK	0.8041	0.9998	0.1957
NCRIME	0.9833	1.0073	0.0238
NNOISE	0.9833	0.9981	0.0147
NLITTER	0.9833	0.9944	0.0111
NWHITE	0.7854	0.9999	0.2145
SCHCOLL	0.9198	0.9989	0.0791
MKTVALUE	0.3114	0.8011	0.6112

Table 8
Variance of Exogenous Variables

Parameter[a]	Estimate	t-value
$\hat{\sigma}^2_{nq}$	0.0790	2.97
$\hat{\sigma}^2_{\zeta}$	0.3114	11.45
$\hat{\sigma}^2_{\epsilon_1}$	0.1988	8.91
$\hat{\sigma}^2_{\epsilon_2}$	0.2651	11.73
$\hat{\sigma}^2_{\delta_1}$	0.9833	34.41
$\hat{\sigma}^2_{\delta_4}$	0.8041	16.65
$\hat{\sigma}^2_{\delta_5}$	0.9198	18.66
$\hat{\sigma}^2_{\delta_6}$	0.7854	15.50

[a]These estimates were obtained imposing the following restriction: $\hat{\sigma}^2_{\delta_1} = \hat{\sigma}^2_{\delta_2} = \hat{\sigma}^2_{\delta_3}$.

Table 9
Correlations among Exogenous Variables

	TAMPA	MIAMI	UNITSF	GARAGED	ROOMS	NBATHS	FPLWKD	PORCHD	AIRCONDS	USFT	USFN
MIAMI	-0.274										
UNITSF	-0.235	-0.071									
GARAGED	0.138	-0.195	0.249								
ROOMS	-0.174	-0.147	0.649	0.253							
NBATHS	-0.180	-0.000	0.471	0.189	0.494						
FPLWKD	-0.234	-0.290	0.402	0.235	0.417	0.380					
PORCHD	-0.143	-0.025	0.220	0.172	0.138	0.217	0.217				
AIRCONDS	-0.053	-0.070	0.241	0.140	0.173	0.412	0.236	0.136			
USFT	0.917	-0.251	-0.066	0.176	-0.039	-0.044	-0.133	-0.067	0.036		
USFN	-0.296	-0.203	0.134	-0.110	0.141	0.051	-0.020	0.005	0.049	-0.272	
NQUALITY	0.012	-0.040	0.107	0.102	0.058	0.106	0.124	0.052	0.141	0.030	-0.029